# Development of internet of vehicles and recurrent neural network enabled intelligent transportation system for smart cities

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**ABSTRACT**

The number of deaths has increased as a direct result of the increased frequency of traffic accidents, congestion, and other risk factors. Developing countries have prioritised the development of intelligent transport systems in order to reduce pollution, traffic congestion, and wasted time. This article describes an intelligent transport system that leverages the internet of vehicles (IoV) and deep learning to forecast traffic congestion. Data is acquired using a car's global positioning system (GPS), road and vehicle sensors, traffic cameras, and traffic speed, density, and flow. All acquired data is stored in one location on a cloud server. The cloud server also stores historical traffic, road, and vehicle data. Using particle swarm optimisation, features are improved. The optimised dataset is used to train and test recurrent neural networks (RNNs), support vector machines (SVMs), and multi layer perceptrons (MLPs). A deep learning algorithm can predict traffic congestion and make recommendations to drivers on how fast to travel and which route to take. The experimental effort employs the performance measurement system (PeMS) traffic dataset. RNN has achieved accuracy of 95.1%.



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## 1. INTRODUCTION

The number of vehicles on the road continues to rise on a daily basis. There has been an increase in the number of fatalities as a direct result of the increased frequency of traffic accidents, congestion, and other related factors. In the last ten years, there has been a significant increase in the number of accidents that have occurred. The number of people who lose their lives as a result of accidents is increasing, even in industrialised countries that have state-of-the-art infrastructure [1]. Accidental deaths are much more common in countries with lower and middle incomes. As a consequence of this, it is essential for less developed countries to place

a high priority on road safety. The growth of the internet of everything (IoE) has been beneficial to both the creation of smart cities as well as intelligent transportation systems (ITS). With the aid of the global positioning system (GPS), it is possible to ascertain both the whereabouts of individual vehicles and the patterns of traffic GPS. The majority of today's autos come pre-fitted with a GPS system that is operational and ready to be used. The massive amounts of data that are generated in real time may be archived with the assistance of fog computing [2]. Internet of vehicles (IoV) scenario is presented in Figure 1. IoV is able to easily manage massive volumes of data inside complex systems as a direct result of this feature. The ITS service will be built using IoV's vehicular ad hoc networks (VANET) as its foundation. The supplemental component of IoV known as telemetry in vehicles makes it possible for messages, payloads, and data to be sent from one moving vehicle to another. In most cases, the supplemental data, which may comprise a vehicle's geo position, spatial-worldly area, route, and remote observation data, will be provided by the vehicle itself [3]. Various features of ITS is shown in Figure 2.

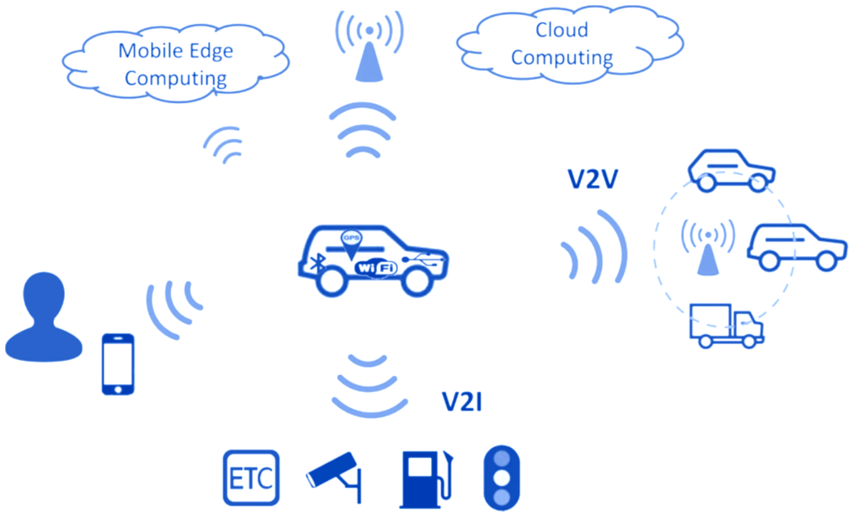


Figure 1. IoV for ITS

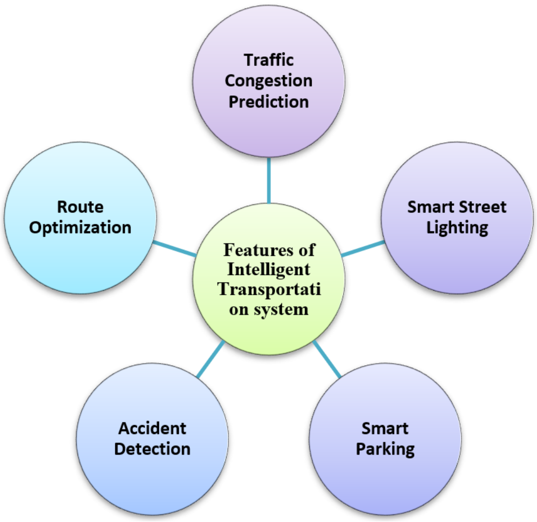


Figure 2. Features of ITS

The expansion of IoE and extensive reliance on sensors made a significant contribution to the simplification of the situation. Developing countries have made the development of an ITS a top priority because they aim to reduce pollution, the amount of time spent sitting in traffic, and lost time. Making decisions

in real time is very necessary for the development of a successful ITS [4]. The government is now making investments in infrastructure technology that can locate the "red zone" for potential accident sites and activate an intimation system to guarantee a prompt response. It's also possible that if the sensors become damaged, they won't be able to provide an accurate diagnostic. Getting to the bottom of the issue and devising strategies to head off any and all future mishaps on the roads is a laborious and time-consuming endeavour. It is almost always better to take precautions to avoid undesirable outcomes rather than to cope with the consequences of such outcomes [5].

The IoV aims to accomplish the creation of a network that may be established between a vehicle and other objects, as well as the infrastructure required for the exchange of data and information between connected devices [6]. The actual goal of the Internet of Cars is to populate the state of man-vehicle-thing with a diverse assortment of goods, vehicles, and other forms of infrastructure. IoV is used for the management of traffic, the development of intelligent dynamic data communication between vehicles, the prevention of road accidents, the management of road health, the conservation of energy, and the protection of the environment as part of ITSs [7].

IoE's combination of speed and efficiency has led to its widespread adoption in a variety of contexts. The IoE has a wide range of potential applications in the automotive and road infrastructure industries, including intelligent traffic monitoring, intelligent braking systems, and self-driving automobiles, to name just a few. IoE is also used to human health, where it is used to create patient-specific monitoring, a strategic medication-recommendation framework, and a perceptive clinical-thinking structure. In addition, IoE is also applied to animal health, where it is used to diagnose and treat animal diseases. The wise, shrewd belt, and brilliant band are all examples of ingenious pieces of wearable technology that have the capability to monitor the status of people's health [8], [9].

This article presents an ITS for traffic congestion prediction that utilises IoV and deep learning. Data is obtained through the utilisation of vehicle GPS data, sensors strategically placed on road infrastructure and cars, traffic cameras, as well as metrics such as traffic speed, traffic density, and traffic flow. The IoV utilises VANET and wireless sensor networks (WSN) for data collecting. A centralised cloud server is utilised for the storage of all gathered data. The cloud server also stores previous data pertaining to traffic, road conditions, and cars. particle swarm optimisation is used to optimise features. The optimisation of a dataset was used to train and evaluate recurrent neural network (RNN), support vector machine (SVM), and multi layer perceptron (MLP). A deep learning model is utilised to forecast traffic congestion and provide recommendations about travel speed and route suggestions. These recommendations are then transmitted to vehicle drivers using a mobile application. The experimental work utilises the performance measurement system (PeMS) traffic dataset. The accuracy of the RNN is 95.1% and better than the accuracy of MLP and SVM algorithms.

## 2. LITERATURE SURVEY

The operators, end-users, product creators, and policy implementers are all working together to strike a balance between the conflicting aims of minimising privacy and security issues while simultaneously maximising the benefits of adopting the most recent and cutting-edge technologies. It is possible that the term "IoE" may be interpreted in many different ways when used in this setting. IoE is defined as a global infrastructure of networked devices employing both known and emerging technologies and their accompanying practical data to provide adequate communication by the International Telecommunication Union (ITU) [10]. Machine-to-machine (M2M) transcends its status as a simple subset of IoE when intelligent technologies are taken into consideration. IoE has finally made its appearance, although with a thud, after more than two decades of acknowledgement, discussion, and controversy. The initial development of IoE focuses on making strides in wireless technology as well as nanotechnology. In the most recent decade, wireless devices such as mobile phones have been talking with other intelligent devices, creating the framework for a strong IoE.

The IoE [11] concept has lately garnered a lot of interest due to the fact that it has the capability of networking hardware that was previously spread out. Let them successfully collect data, send it to a server, process it, and utilise it to their benefit by giving them permission to do so. The rise of the IoE has also been a driving force behind the creation of intelligent electronic products. In addition to the benefits and drawbacks associated with smart devices and smart cities, the IoE also has an impact on the social lives of regular people. Only a few examples of the IoE include internet-connected autos, embedded devices that can be managed remotely, smart transportation systems, and other similar applications.

The "IoE" is simply the basis upon which Internet-enabled devices may speak with one another and exchange data with one another. This is what we mean when we say "IoE". Information is sent back and forth between and among abstract concepts and the physical nodes that make up IoE. IoE is analogous to a network of railroad lines, replete with stops and interchanges at various points along the route. The general notion of integrating diverse digital nodes of varied capacities and running via the internet is what is meant by the phrase "IoE". The communication that takes place between machines is just a small component of the whole picture.

At this point in time, there are more nodes connected to the IoE network than there are users. Examples of CICSO's pioneering work in this field include smart transportation, an intelligent grid, and other similar developments. An IoE network or architecture is made up of a multitude of nodes, communication rules, and clusters. Connectivity in the Internet of Things (IoT) may be accomplished by the use of a variety of different directed technologies, such as WiMax and ZigBee, amongst others. The current internet infrastructure will get enhancements thanks to the IoE's addition of additional dimensions [12].

In addition, a number of the behavior-driven systems that were covered in [13] required an efficient approach for determining the best possible path. The vast volumes of traffic that exist in cities make it very essential to choose the most effective option that is available. This approach is becoming more prevalent in research settings. The approach developed by Dijkstra is often used at the beginning of the process in order to discover the most efficient path from the point of origin to the final destination. This method is based on a very simple premise: it finds every viable route between the origin and the destination, calculates the cost of each path, and then returns the final path that has the lowest overall cost. This algorithm is based on a very simple idea. The Dijkstra algorithm has served as the basis for the development of a great many other cutting-edge algorithms. The method for determining the shortest path occurs in many different problem descriptions. One of the problems, for instance, is referred to as the vehicle routing problem.

A shift toward the use of artificial intelligent and machine learning has recently taken place. The fundamental tenet of this approach is known as reinforcement learning. During the course of the previous decade, a number of distinct types of intelligent reinforcement algorithms have arisen, each of which is able to make judgments on its own, in a manner that is analogous to that of a person. We read about the instant-similar-based hybrid genetic algorithm that was built to produce an optimum route utilising correlation-linked speculative path architecture [14]. This method is described as having been developed by researchers. It is possible to construct connections between nodes and edges via the application of correlation coefficients [15]. The evolutionary algorithm is built to use a meta-heuristic method, which searches the area immediately around each node, in order to discover the optimal route that may possibly be taken. An optimization strategy that is based on a hybrid particle swarm is presented in the paper [16]. This strategy conducts a search for neighbouring vertices in order to identify the best possible solution. The setting of limitations is made possible by using this strategy. A technique to route discovery for particle swarm optimization (PSO) that is focused on finding the Pareto-optimal solution may be found in [17]. It was postulated in [18] that an artificial neural network with a time-delay may provide the optimum route to take under time constraints. Even when there is a disagreement, the neural network is still able to find the vertices in the research [19]. Predictions have been made on the future circulation patterns of traffic [20]. After perusing the pertinent literature, it becomes clear that there is a requirement for an algorithm for determining the shortest route that is capable of automatically making the most appropriate decisions based on historical information and can adjust to dynamic traffic conditions that are always evolving.

## 3. METHOD

This section provides IoV and deep learning enabled ITS for traffic congestion prediction. Data is acquired from vehicle GPS data, sensors deployed on road infrastructure and vehicles, traffic cameras, traffic speed, traffic density, traffic flow. IoV is used in data acquisition using VANET and WSN. All acquired data is stored in a centralized cloud server. Cloud server also contains historical data related to traffic, road and vehicles. Features are optimized by applying PSO. Training and testing of RNN, SVM, and MLP by optimized dataset [21]. Deep learning enabled model is predicting traffic congestion and recommendation related to travel speed and route suggestion is send using mobile application to vehicle driver. Figure 3 presents proposed methodology for ITS for traffic congestion prediction.

While convolutional neural networks (CNNs) succeeds with spatial data, RNN shines with sequential data. RNNs are equipped with their own memories, allowing them to draw lessons from their past experiences and enhance their capabilities when presented with fresh data. The principal uses are language modelling, problems with prediction, and data derived from text. RNN technology has been integrated into consumer goods such as Apple's Siri and Google's very own voice assistant. Because it works in random access memory (RAM), this algorithm is perfect for handling sequential information because it can organise it in a logical fashion. It is the only method for machine learning that can store data in its own memory, and it is a very strong one. RNNs are able to make reliable projections about the future of the system because they are able to recall significant aspects of the data they are fed. RNNs, in contrast to many other algorithms, are particularly effective when dealing with information that is sequential. We refer to this kind of neural network as a feed-forward neural network due to the fact that it only employs forward propagation from the input layer to the output layer.

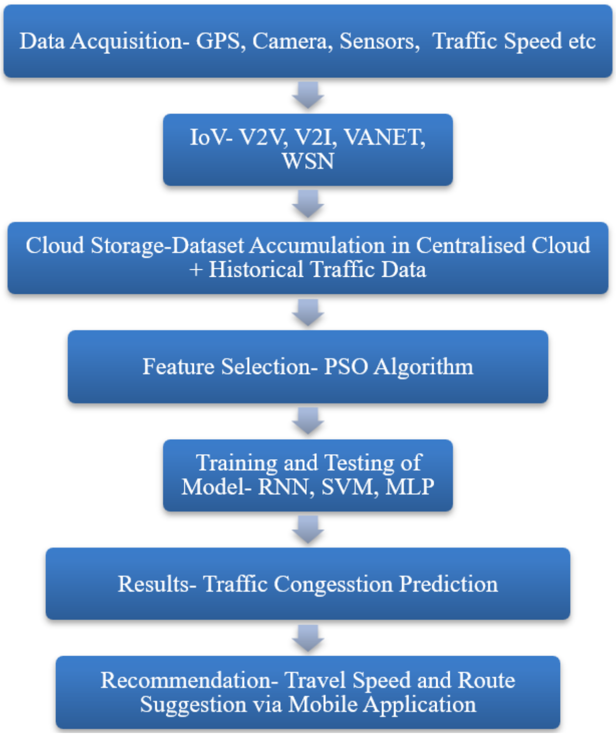


Figure 3. IoV and deep learning enabled ITS for traffic congestion prediction

The standard neural network diagnostic and treatment procedures are useless in this context. RNNs are distinguished from other neural networks in that they may be applied to a time-varying vector sequence [22]. RNN is shown in Figure 4. RNNs, often known as RNNs, are a subclass of neural networks that are optimised for tackling difficulties related to sequence. You may think of a RNN as an extension of a standard feedforward multilayer perceptron network by putting in some loops. This is one approach to conceptualise a RNN. For example, a neuron in one layer may send its signal not just vertically to the layer above it, but also laterally to the cells that are next to it. It is possible that the output of the network will be included as an extra input in the succeeding input vector. The recurrent connections operate as a type of memory for the network, which enables it to learn higher-level abstractions based on the sequences of information that are input. The field of RNNs is well established, and there are a number of standard, accepted methods. To be more specific, the backpropagation through time (BPTT) approach is used in the process of instructing RNNs.

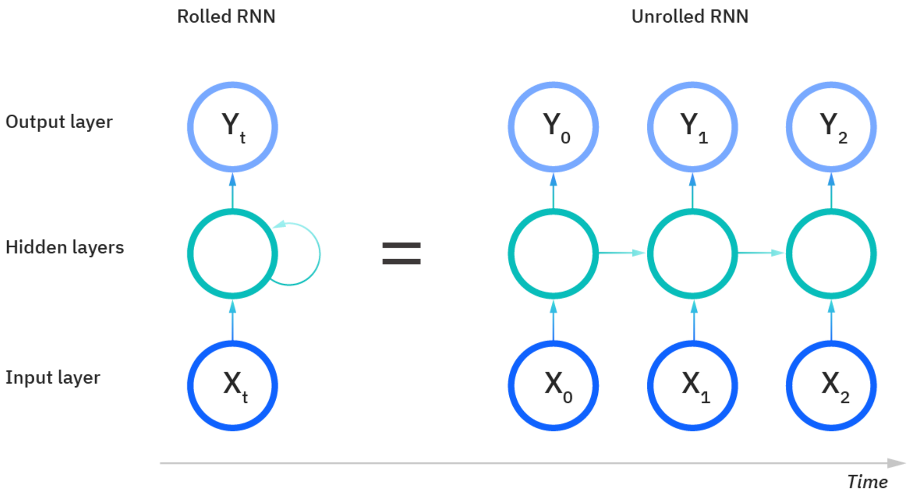


Figure 4. RNN

With the assistance of the SVM approach [23], [24] it is possible to locate hyperplanes in N-dimensional space with more ease. In addition to this, it distinguishes between individual discrete data components. The SVM algorithm constructs the border of the best judgement line in order to classify newly collected data points into the appropriate category. This allows the programme to correctly classify newly collected data points. This particular horizontal or vertical line is referred to as a "hyperplane". The most common uses for this method are in the areas of face recognition, image categorization, and text recognition. Similarly, the size of the hyperplane is established by the interaction of a number of different elements. If there are just two characteristics used to generate the hyperplane, it will seem like a straight line. When there are three characteristics used to form the hyperplane, the hyperplane loses a dimension and becomes two-dimensional. This happens when the number of characteristics used to generate the hyperplane climbs to three. It is impossible to complete the assignment if more than three attributes are given as input. By making use of these vectors, author able to increase the margin of the classifier. In the event that the support vectors are deleted, the position of the hyperplane may be modified. These things to think about will be helpful in the process of building SVM. The SVM, approach was developed with the intention of improving the correlation that existed between the data points and the hyperplanes. Increases in margin are possible with the assistance of hinge loss. If the signs of the predicted and actual numbers are the same, there is no cost associated with it. If this is not the case, then the classifiers will decide whether or not there was a loss. By include the regularisationoption, the cost function is also changed in this iteration of the process. The regularisation settings make an effort to give the impression that maximising margin and minimising loss are about equivalent goals. We make use of partial derivatives with weights in conjunction with a loss function in order to emphasise the gradients. We are able to improve weights by using gradients. If misclassification is the primary issue, it is required to modify the gradient using a regularisation parameter. This indicates that the model is accurate and can properly predict the class of data points.

By analysing this network, it is possible to have a better understanding of the fundamental issues that are affecting contemporary deep learning models. To be more specific, the feed-forward ANN serves as the basis for it. When there is just one hidden layer inside a neural network, we refer to this configuration as "vanilla". The term "multilayer neural network" refers to a multilayer that does not include even a single perceptron in its structure MLP. When constructing mathematical models, regression analysis should be used. MLP is not the most effective method to utilise for analysing patterns when dealing with data that is sequential as well as multi-dimensional.

## 4. RESULTS AND DISCUSSION

PeMS [25] traffic dataset is used in this experiment. Every major city in California is home to at least one of the over 40,000 individual detectors that are dispersed throughout the state’s highway system. These detectors capture data in real time. Features are optimized by applying PSO. Training and testing of RNN, SVM and MLP by optimized dataset. Deep learning enabled model is predicting traffic congestion and recommendation related to travel speed and route suggestion is send using mobile application to vehicle driver. PeMS traffic dataset is used in the experimental work. RNN has achieved better accuracy. Results are presented in Tables 1-3 and Figure 5.

Table 1. Accuracy comparison of PSO RNN, PSO SVM, and PSO MLP for traffic congestion prediction

| Algorithm | Classification accuracy (%) |
|---|---|
| PSO RNN | 95.1 |
| PSO SVM | 91.2 |
| PSO MLP | 83.7 |

Table 2. Sensitivity comparison of PSO RNN, PSO SVM, and PSO MLP for traffic congestion prediction

| Algorithm | Sensitivity (%) |
|---|---|
| PSO RNN | 94.7 |
| PSO SVM | 90.3 |
| PSO MLP | 83.9 |

Table 3. Specificity comparison of PSO RNN, PSO SVM, and PSO MLP for traffic congestion prediction

| Algorithm | Specificity (%) |
|---|---|
| PSO RNN | 94.9 |
| PSO SVM | 93.3 |
| PSO MLP | 88.5 |

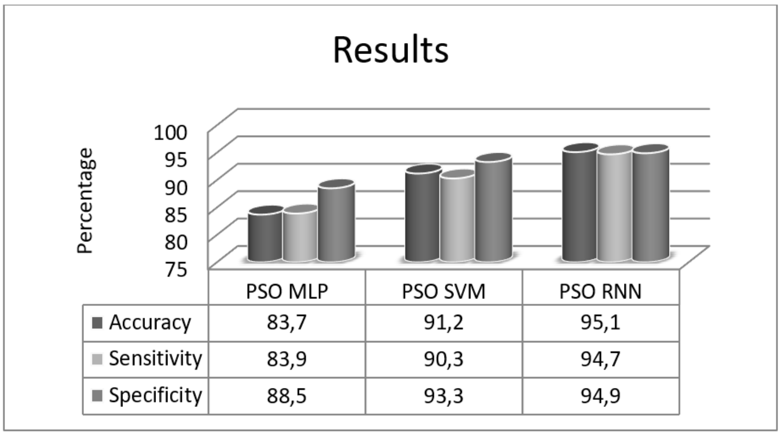


Figure 5. Comparison of PSO RNN, PSO SVM, and PSO MLP for traffic congestion prediction

The confusion matrix is a useful tool for seeing how well various machine learning approaches work. The confusion matrix may determine one of four possible outcomes, denoted by the letters true positive (TP), false negative (FN), true negative (TN), and false positive (FP). The phrase "TP" describes a situation in which the model has identified a specific quantity of data as positive and that data really is positive. When all of a dataset's categories are labelled as "negative", we say that the dataset is "true negative".

The number of instances when information was mistakenly labelled as positive when it was really negative is another definition of a FP. In conclusion, a FN is a representation of the fact that the amount for the data is negative and is classified as negative. The phrase "type 1 error" is also often used to describe to a "false positive". The FN error, also known as form 2 error, is a common type of error. Classification accuracy, precision, recall, and F1 score are all metrics that may be used to evaluate modern machine learning and transfer learning strategies, including deep CNN.

Accuracy in classification is measured as a percentage of training pictures that are correctly categorised compared to the total number of test images produced by the classification models. As a result, the classification might be right anywhere from 0% to 100% of the time.

$$Accuracy = (TP + TN)/(TP + TN + FP + FN)$$

## 5. CONCLUSION

The expansion of the IoT has been advantageous not only to the development of smart cities but also to the advancement of ITSs IoE. It is possible, with the assistance of the GPS, to identify both the positions of individual cars as well as the patterns of traffic GPS. The IoV project's goal is to realise the creation of a network that can be established between a vehicle and other objects, in addition to the infrastructure required for the exchange of data and information between connected devices. This network can be established between a vehicle and other things. This article provides a description of an ITS that makes use of the IoV and deep learning to forecast where and when traffic congestion may occur. The GPS of a vehicle, sensors on the road and on cars, traffic cameras, as well as the speed, density, and flow of traffic, all contribute to the collection of data. Data from the IoV may be obtained via the usage of VANET as well as WSN. A cloud server stores all of the information that has been gathered in a centralised location for easy access. The cloud server also stores historical data on the cars, roads, and traffic that existed in the past. PSO is used to improve the qualities of the characteristics. The RNN, the SVM, and the MLP are all trained and tested with the use of an optimised dataset. Deep learning makes it possible for a model to anticipate the formation of traffic bottlenecks and provide drivers with advice on the appropriate speed at which they should travel and the best route to follow to avoid the jams. The PeMS traffic data collection is being used in the experimental study. The RNN has significantly improved its ability to correctly predict outcomes.

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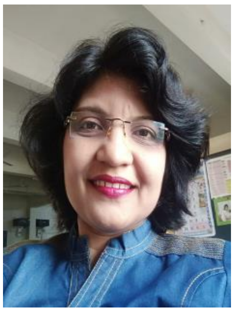

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